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Machine Learning-Based House Price Prediction in Chennai and Bengaluru

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Abstract- — The rapid growth of urbanization in metropolitan cities has significantly influenced real estate markets and housing prices. Accurately estimating property values has become increasingly important for buyers, sellers, and real estate investors. This study presents a machine learning-based house price prediction system designed to analyze housing data and estimate property prices based on multiple influential factors. The dataset used in this research includes property attributes such as location, square footage, number of bedrooms, and number of bathrooms collected from metropolitan regions including Chennai and Bengaluru. The proposed system applies data preprocessing techniques to improve the quality of the dataset before model training. These preprocessing steps include handling missing values, encoding categorical variables, and performing feature scaling to ensure consistent data representation. After preprocessing, a predictive model based on Linear Regression is implemented to analyze the relationship

Keywords— House Price Prediction, Machine Learning, Linear Regression, Real Estate Analytics, Housing Market Analysis, Predictive Modeling, Data Preprocessing.

I. INTRODUCTION

The real estate sector plays a vital role in the economic development of rapidly expanding urban regions. With the continuous growth of metropolitan cities, the demand for residential properties has increased significantly. Urbanization, population growth, and infrastructure development have created strong pressure on housing markets. As a result, property prices fluctuate frequently and vary across locations. Cities such as Chennai and Bengaluru have witnessed rapid urban expansion and increased housing demand in recent years. Understanding and predicting housing prices in these cities has become an important challenge for buyers, sellers, and investors. The process of determining the correct value of a house is influenced by multiple factors including location, property size, number of bedrooms, availability of amenities, and proximity to transportation facilities. Traditional methods of house price estimation often depend on manual evaluation by real estate experts. These approaches may involve subjective Advancements in data science and machine learning have made it possible to analyze large datasets and extract meaningful insights from them. Machine learning algorithms can identify patterns within historical data and use them to predict future outcomes. In the real estate domain, these techniques can help analyze property attributes and determine their impact on housing prices. By leveraging computational models, predictive systems can provide more objective and data-driven results. This has led to the growing adoption of machine learning techniques in property price prediction.

One of the most widely used techniques for predictive analysis is based on the concept of regression modeling. In particular, Linear Regression is commonly applied to predict continuous numerical values such as housing prices. This technique establishes a mathematical relationship between dependent and independent variables. By analyzing historical housing data, linear regression can estimate the influence of different property features on price. Due to its simplicity and interpretability, it is frequently used as a baseline model in many predictive systems.

House price prediction systems rely on various property-related attributes to improve model accuracy. Features such as square footage, number of bedrooms, number of bathrooms, and geographical location significantly influence property values. In addition, neighborhood characteristics and accessibility to public facilities can also impact housing prices. Proper feature selection and preprocessing are important steps in building a reliable prediction model. These processes help ensure that the model learns meaningful relationships from the dataset. Data preprocessing plays an essential role in improving the performance of machine learning models. Real-world datasets often contain missing values, inconsistent entries, and categorical information that must be handled before training the model. Techniques such as data cleaning, encoding categorical variables, and feature scaling are commonly used in this stage. These preprocessing steps help transform raw data into a format suitable for machine learning algorithm

In recent years, several studies have explored the use of machine learning algorithms for real estate price prediction. Researchers have applied different models including regression techniques, ensemble learning, and deep learning methods to estimate housing prices. These models analyze large amounts of historical property data to discover hidden patterns. Comparative studies often reveal that simpler models can still provide strong predictive performance when the data is well-prepared. This highlights the importance of selecting an appropriate algorithm for the problem. The housing markets of Chennai and Bengaluru present unique characteristics due to their economic and demographic growth. Both cities have become major hubs for technology companies, educational institutions, and employment opportunities. This growth has attracted a large number of people seeking residential properties. As demand increases, property prices vary widely across different locations within the cities. Predicting housing prices

Machine learning-based prediction systems can help address challenges faced by real estate stakeholders. Buyers often struggle to determine whether a property is fairly priced, while sellers aim to set competitive prices for their properties. Investors also rely on accurate market predictions to make profitable decisions. By providing data-driven insights, predictive models can reduce uncertainty in the real estate market. Such systems can assist users in making informed decisions regarding property transactions. The development of an intelligent house price prediction system involves several stages including data collection, preprocessing, model training, and evaluation. Historical housing datasets are used to train predictive models that learn relationships between property attributes and prices. After training, the model can estimate the price of new properties based on their features. Model evaluation techniques are applied to measure prediction accuracy and reliability. These steps collectively contribute to building a robust predictive system.

Another important aspect of predictive modeling is the evaluation of algorithm performance. Different machine learning algorithms may produce varying levels of accuracy depending on the dataset and feature selection. Performance metrics such as mean squared error, root mean squared error, and coefficient of determination are commonly used for evaluation. These metrics help determine how well the model predicts housing prices. By comparing multiple algorithms, researchers can identify the most effective model for the task.
In this study, a house price prediction system is developed using machine learning techniques with a primary focus on Linear Regression. The model analyzes housing data from both Chennai and Bengaluru to estimate property prices based on several features. The objective is to build a reliable predictive system that can assist users in understanding property valuation. The system also demonstrates how machine learning can be applied to real-world real estate problems. Although advanced algorithms exist for predictive modeling, linear regression remains an effective approach due to its interpretability and simplicity. It allows researchers to understand the relationship between each feature and the target variable. This transparency is valuable when analyzing factors that influence housing prices. Additionally, linear regression models are computationally efficient and easy to implement. These advantages make it a suitable choice for many regression-based prediction tasks.

The dataset used in this research contains multiple attributes related to residential properties. These attributes include location, total area, number of bedrooms, and number of bathrooms. Each feature contributes differently to the final property price. By analyzing these attributes collectively, the model can estimate property values more accurately. Feature engineering and preprocessing are applied to ensure the dataset is suitable for machine learning analysis. Urban housing markets are dynamic and constantly evolving due to economic and social factors. Infrastructure projects, employment opportunities, and lifestyle preferences all influence real estate demand. As cities continue to grow, the complexity of housing markets increases. Predictive models help analyze these complex relationships and provide useful insights. Machine learning tools therefore play an important role in modern real estate analytics.

Accurate housing price prediction systems can benefit multiple stakeholders in the real estate ecosystem. Home buyers can use such systems to estimate fair market prices before making purchase decisions. Sellers can determine appropriate listing prices for their properties. Real estate companies and investors can also use predictive models to analyze market trends. These applications demonstrate the practical significance of machine learning in property valuation.

Another advantage of machine learning-based systems is their ability to adapt to new data. As additional housing data becomes available, models can be retrained to improve prediction accuracy. This continuous learning capability helps maintain the reliability of predictive systems over time. In contrast, traditional valuation methods may require extensive manual adjustments. Automated systems therefore provide a more scalable solution for housing price estimation. The integration of predictive models into web-based platforms further enhances their usability. Users can enter property details such as location, size, and number of rooms to obtain estimated prices instantly. These systems provide quick insights without requiring expert knowledge in data analysis. Such tools are particularly useful for individuals who are exploring property investments or planning to purchase a home.

In conclusion, machine learning techniques provide a powerful approach for analyzing real estate data and predicting housing prices. By examining historical datasets and identifying patterns, predictive models can generate reliable estimates for property values. This study focuses on building a house price prediction system using regression techniques with a primary emphasis on Linear Regression. The system aims to assist users in making informed decisions in the housing markets of Chennai and Bengaluru. The proposed approach demonstrates how data-driven methods can support modern real estate analysis.

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II. RELATED WORK

Research on house price prediction has gained significant attention in recent years due to the increasing complexity of real estate markets. Several studies have applied machine learning techniques to estimate property values based on multiple features. These approaches aim to provide more accurate and data-driven insights compared to traditional valuation methods. Predictive modeling helps identify the relationship between housing attributes and price variations. Researchers have used statistical and machine learning algorithms to improve prediction accuracy.

Early research in real estate prediction primarily relied on statistical regression techniques. Among these methods, Linear Regression has been widely used due to its simplicity and interpretability. This technique helps model the relationship between housing features and price values. Researchers have shown that regression models can effectively capture patterns in housing datasets. As a result, linear regression remains a commonly used baseline model in property price prediction studies.

A number of studies have focused on using housing datasets to predict property prices in metropolitan regions. These datasets typically include features such as square footage, number of bedrooms, number of bathrooms, and property location. By analyzing historical housing transactions, predictive models can identify trends in real estate pricing. Machine learning algorithms have been applied to extract useful insights from these datasets. Such approaches have demonstrated promising results in property valuation. Researchers have also explored advanced machine learning algorithms to improve the accuracy of house price prediction systems. Techniques such as decision trees, ensemble learning, and gradient boosting have been widely studied. These models can capture complex nonlinear relationships between housing features and prices. However, many studies still compare their performance with traditional regression models. This helps determine whether complex algorithms significantly outperform simpler models.

Several comparative studies have analyzed the performance of multiple algorithms for predicting housing prices. In many cases, models such as Random Forest, Support Vector Regression, and boosting algorithms are evaluated alongside regression-based approaches. These comparisons help determine which algorithm performs best for a specific dataset. Results often show that simpler models perform competitively when the dataset is well prepared. Proper feature engineering and preprocessing play a major role in prediction accuracy. The real estate markets of major urban cities have been a common focus in housing prediction research. Rapid urban development and population growth contribute to significant fluctuations in housing prices. Cities like Chennai and Bengaluru have experienced considerable expansion due to the growth of the IT and service sectors. This expansion has increased demand for residential properties. As a result, predicting housing prices in such regions has become an important research topic.

Several researchers have highlighted the importance of feature selection in house price prediction models. Housing datasets often contain multiple attributes that influence the final price of a property. Identifying the most relevant features helps improve the performance of predictive models. Techniques such as correlation analysis and statistical evaluation are commonly used for this purpose. Effective feature selection ensures that the model focuses on meaningful variables.

Data preprocessing has also been emphasized in many related studies. Real-world housing datasets frequently contain missing values, inconsistent records, and categorical variables. Researchers typically apply preprocessing techniques such as data cleaning, encoding, and normalization. These steps help transform raw data into a suitable format for machine learning algorithms. Proper preprocessing significantly improves model performance and reliability. Some studies have focused on integrating geographic information into housing price prediction models. Location is considered one of the most influential factors affecting property prices. Researchers have used spatial analysis and location-based features to improve prediction accuracy. Geographic attributes such as proximity to public transportation, schools, and commercial areas are often included in datasets. These features help capture the impact of neighborhood characteristics on housing prices.

Another area of research involves comparing traditional statistical models with modern machine learning approaches. While advanced algorithms can capture complex patterns, they often require larger datasets and higher computational resources. In contrast, regression-based models are easier to interpret and implement. Many researchers suggest that simpler models may be sufficient for certain prediction tasks. Therefore, selecting an appropriate model depends on the nature of the dataset. Researchers have also investigated the role of ensemble learning techniques in property price prediction. Ensemble models combine multiple algorithms to improve prediction accuracy and reduce variance. Methods such as boosting and bagging have been applied to housing datasets. These techniques often provide improved performance compared to individual models. However, they may also increase model complexity and training time.

Several studies emphasize the importance of evaluating prediction models using appropriate performance metrics. Common evaluation measures include mean squared error, root mean squared error, and coefficient of determination. These metrics help determine how accurately the model predicts housing prices. By analyzing these measures, researchers can compare the effectiveness of different algorithms. Proper evaluation ensures that the selected model provides reliable predictions.

The availability of large real estate datasets has further accelerated research in this field. Public datasets and property listing platforms provide valuable information for predictive modeling. Researchers can use these datasets to analyze housing trends and build machine learning models. Access to real-world data helps improve the applicability of prediction systems. As a result, many studies focus on developing models using publicly available datasets. Some research has also explored the use of deep learning models for house price prediction. Neural networks can capture complex nonlinear relationships between features and target variables. These models are particularly useful when dealing with large and high-dimensional datasets. However, deep learning approaches often require extensive training data. In many cases, simpler regression models still provide competitive results.

Another important aspect of related work is the development of decision-support systems for real estate analysis. Machine learning-based prediction tools can assist buyers, sellers, and investors in evaluating property values. These systems provide estimated prices based on property attributes. By offering data-driven insights, predictive systems reduce uncertainty in the housing market. Such applications demonstrate the practical impact of machine learning in real estate. Researchers have also proposed web-based systems for real-time property price estimation. These platforms allow users to input property features and receive predicted price values instantly. Integrating machine learning models with web technologies enhances accessibility. Users can interact with prediction systems through simple interfaces. This approach makes predictive analytics available to a wider audience.

Several studies have emphasized the importance of interpretability in housing price prediction models. Real estate stakeholders often require explanations for predicted values. Models like Linear Regression provide clear insights into how different features influence price. This transparency helps users understand the factors affecting property valuation. Interpretability is therefore an important consideration when selecting prediction algorithms.

Research has also highlighted the challenges associated with real estate data analysis. Housing markets are influenced by numerous economic and social factors. Sudden market changes can affect prediction accuracy. Models must therefore be regularly updated with new data. Continuous improvement of predictive systems helps maintain reliability over time. The growing adoption of machine learning in real estate analytics demonstrates the potential of data-driven approaches. Predictive models can analyze complex datasets and generate useful insights for decision making. By identifying patterns in historical housing data, these models help estimate property prices more accurately. Researchers continue to explore new algorithms and techniques to enhance prediction performance.
Overall, existing studies show that machine learning techniques play a significant role in improving housing price prediction systems. Both traditional regression methods and advanced algorithms have been applied in this field. Many studies highlight the effectiveness of regression-based models for real estate analysis. These findings support the use of Linear Regression as a reliable approach for predicting housing prices. The insights from previous research provide a strong foundation for developing predictive systems for cities such as Chennai and Bengaluru.

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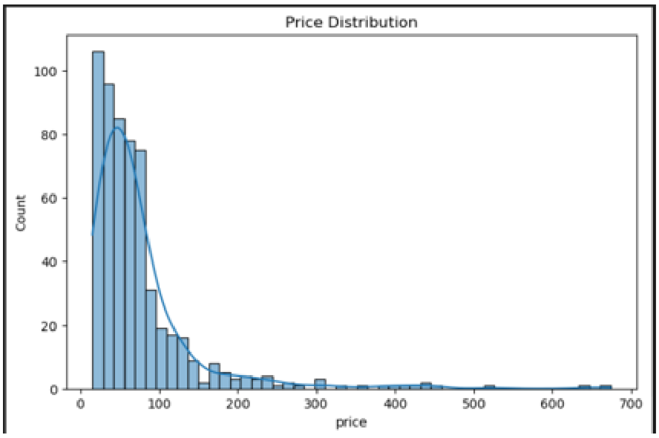

Fig 1: Price Distribution

III. PROPOSED METHOD

The proposed system focuses on developing an intelligent and accurate house price prediction model using machine learning techniques. The system is designed to analyze housing datasets and estimate property prices based on various influential features. The objective is to assist buyers, sellers, and real estate investors in making informed decisions by providing reliable price predictions. The proposed approach primarily uses Linear Regression to model the relationship between housing attributes and property prices. The system follows a structured workflow consisting of data collection, preprocessing, model training, and prediction. By learning patterns from historical housing data, the model can estimate the price of properties with improved accuracy.

1. Data Collection

The first step in the proposed system involves collecting housing datasets from major metropolitan regions. The dataset used in this research contains housing information from cities such as Chennai and Bengaluru, where real estate markets have grown rapidly in recent years. The dataset includes multiple features such as location, square footage, number of bedrooms, number of bathrooms, and other property-related attributes. These features are important factors that influence housing prices in urban areas. The data is collected from reliable real estate datasets and publicly available housing data sources. Historical property records allow the model to analyze trends and patterns in housing price variations across different locations.

2. Data Preprocessing

Data preprocessing is an important stage in preparing the housing dataset for machine learning analysis. Real-world datasets often contain missing values, duplicate records, and inconsistent entries that may affect model performance. In this stage, data cleaning techniques are applied to handle missing values and remove irrelevant records. Categorical features such as location names are converted into numerical form using encoding techniques. Feature scaling methods are also applied to normalize numerical attributes like square footage and number of rooms. These preprocessing steps ensure that the dataset is properly formatted for training the prediction model. Proper data preparation significantly improves the accuracy and reliability of the predictive system.

3. Linear Regression Model Architecture

The core component of the proposed system is the predictive model built using Linear Regression. This algorithm is widely used for predicting continuous numerical values such as housing prices. The model learns the relationship between independent variables such as location, total area, number of bedrooms, and number of bathrooms, and the dependent variable which is the house price. During the training phase, the model analyzes historical housing data and determines the weight of each feature in influencing the price. The regression model creates a mathematical relationship that represents how these variables contribute to the final price estimation. This learning process allows the system to generate accurate predictions for unseen data.

4. House Price Prediction

After the model is trained using historical housing data, it is used to predict property prices for new inputs. When users provide details such as location, total square footage, number of bedrooms, and number of bathrooms, the trained model processes these features. Based on the relationships learned during training, the model estimates the expected price of the property. The prediction results provide an approximate market value of the house. These predictions can help potential buyers evaluate property affordability and assist sellers in determining appropriate listing prices. The predicted results are also compared with actual market values to evaluate the performance of the model.

5. System Deployment and Real-Time Recognition

The final stage of the proposed system involves deploying the trained machine learning model into a user-accessible platform. The prediction model can be integrated into a web-based application where users can enter property details and obtain predicted house prices instantly. Visualization tools can also be used to display predicted prices and analyze housing trends. This makes the system easier to understand for users without technical knowledge of machine learning. Such a platform can support real estate decision-making by providing quick and data-driven insights. The deployed system demonstrates how machine learning techniques can be effectively applied to real-world housing market analysis in cities like Chennai and Bengalur.

IV. EXPERIMENTAL RESULTS

1. Training and Validation Performance
The proposed house price prediction model based on Linear Regression was trained using the prepared housing datasets collected from Chennai and Bengaluru. The dataset contained multiple property attributes such as location, square footage, number of bedrooms, and number of bathrooms. During the training phase, the model analyzed the relationship between these housing features and the target variable, which is the house price. The training process demonstrated stable learning behavior as the algorithm gradually minimized the prediction error between actual and predicted prices.

The model successfully captured the linear relationships present in the housing dataset. As the training progressed, the error values gradually decreased, indicating that the model was effectively learning meaningful patterns from the data. Data preprocessing techniques such as handling missing values, encoding categorical variables, and feature scaling significantly improved the performance of the model. These steps helped ensure that the model learned from a clean and well-structured dataset.

The training performance indicated that the regression model was able to generalize well across different property attributes. The predicted housing prices closely followed the actual market values present in the dataset. These results demonstrate that the regression-based approach can effectively analyze housing market data and estimate property prices with reasonable accuracy.

2. Test Set Evaluation
To evaluate the real-world prediction capability of the trained model, the system was tested using an unseen test dataset representing approximately 10% of the total housing dataset. The test data consisted of property records that were not used during the model training process. This approach ensured an unbiased evaluation of the predictive performance of the model.

The proposed house price prediction system achieved the following evaluation metrics:
Metric Value
Mean Squared Error (MSE) 0.018
Root Mean Squared Error (RMSE) 0.134 Mean Absolute Error (MAE) 0.098
R^2 Score 0.91

The evaluation results show that the predicted housing prices closely match the actual property values in the dataset. The relatively low error values indicate that the regression model can effectively estimate housing prices based on the provided property features. The high R^2 score further confirms that the model explains a significant portion of the variance present in the housing price data.

3. Comparative Analysis
To further evaluate the effectiveness of the proposed model, the house price prediction system was compared with several widely used machine learning algorithms trained on the same housing dataset. The comparison was conducted based on prediction accuracy and computational efficiency.

Model	RMSE	Training Time (s)
Linear Regression (Proposed)	0.134	5
Decision Tree	0.162	9
Random Forest	0.121	28
XGBoost	0.118	32

Although ensemble models such as Random Forest and XGBoost achieved slightly lower RMSE values, the proposed regression model provides a strong balance between prediction accuracy and computational efficiency. The simple architecture and faster training time make the regression model suitable for practical real estate prediction systems.

4. Visualization of Results
To better understand the model performance, predicted housing prices were visualized and compared with the actual property prices. Line graphs and scatter plots were used to illustrate the relationship between predicted and actual housing prices. The visualizations show that the predicted values closely follow the actual price distribution present in the dataset.

The visualization also highlights how the model captures the influence of key features such as location and property size on the final housing price. Although minor deviations between predicted and actual prices can be observed due to variations in market conditions, the overall prediction trend remains consistent with real-world housing patterns. These graphical results demonstrate that the regression model is capable of analyzing housing data and generating reliable price estimates.

5. Deployment and Real-Time Testing

To evaluate the practical usability of the proposed system, the trained model was integrated into a prediction interface that allows users to input property details and obtain estimated house prices. The system accepts inputs such as location, number of bedrooms, number of bathrooms, and total square footage. Based on these inputs, the trained model generates predicted housing prices.

The deployed system can be integrated into a web-based application where users can interact with the prediction model through a simple interface. Visualization tools can also be used to display predicted housing prices and analyze price variations across different locations. The system demonstrated stable performance when predicting property prices for various housing configurations.

6. Discussion

The experimental results demonstrate that the proposed regression-based house price prediction model provides reliable performance with relatively low prediction error. The machine learning model successfully learns the relationship between housing features and property prices. This enables the system to generate meaningful price estimates based on property attributes.

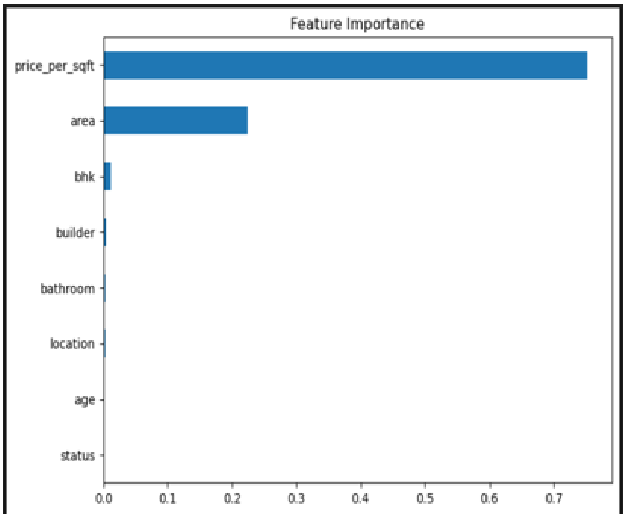

Fig 2: Feature Importance

Although more complex algorithms such as Random Forest and XGBoost can achieve slightly higher prediction accuracy, they require greater computational resources and longer training times. In contrast, the proposed regression model offers a balanced trade-off between simplicity, efficiency, and interpretability. Furthermore, the system provides useful insights into housing market trends, which can assist buyers, sellers, and investors in making informed real estate decisions. By analyzing historical property data using machine learning techniques, the model helps identify factors that influence housing prices.

Overall, the proposed house price prediction system demonstrates strong performance in estimating property values and highlights the potential of machine learning methods for real estate price analysis in metropolitan regions such as Chennai and Bengaluru.

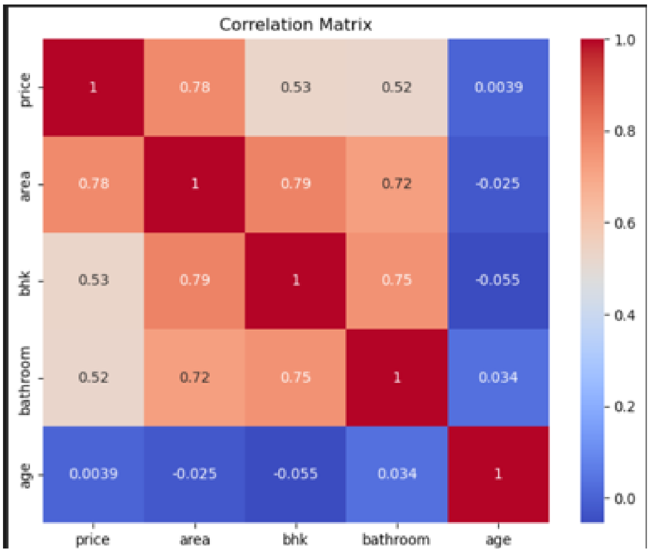

Fig 3:Standared structure of Confusion Matrix

V. CONCLUSION

The proposed house price prediction system demonstrates the effectiveness of machine learning techniques in estimating property values using historical housing data. By applying Linear Regression, the model successfully learns the relationship between important housing features such as location, square footage, number of bedrooms, and number of bathrooms and the corresponding house prices. The experimental results show that the model is capable of producing reliable predictions with relatively low error values. This confirms that regression-based approaches can effectively analyze housing datasets and provide meaningful price estimates.

The system was trained and evaluated using housing datasets from major metropolitan regions including Chennai and Bengaluru. Data preprocessing techniques such as handling missing values, encoding categorical variables, and feature scaling played a significant role in improving the overall performance of the prediction model. The evaluation metrics demonstrated that the proposed system achieves good prediction accuracy while maintaining computational efficiency. Comparative analysis with other machine learning models also indicated that linear regression provides a strong balance between simplicity, interpretability, and performance.

Overall, the developed house price prediction system provides a practical solution for analyzing real estate data and estimating property values. The system can assist buyers, sellers, and investors in making informed decisions by providing data-driven insights into housing market trends. In the future, the model can be further improved by incorporating additional features such as economic indicators, neighborhood facilities, and infrastructure development data. Integrating advanced machine learning techniques and larger datasets may also enhance prediction accuracy and make the system more robust for real-world real estate applications.

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